TRAVERSABILITY INDICES FOR MULTI-SCALE TERRAIN ASSESSMENT

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Abstract: This paper presents novel measures of terrain traversability at three different scales of resolution; namely Local, Regional, and Global Traversability Indices. The Local Traversability Index is related by a set of rules to local obstacles and surface softness, measured by on-board sensors mounted on the robot. The rule-based Regional Traversability Index is computed from the terrain roughness and slope that are extracted from video images obtained by on-board cameras. The Global Traversability Index is obtained from the terrain topographic map and is based on the natural or man-made surface features such as mountains and craters. Each traversability index is represented by four fuzzy sets with the linguistic labels {POOR, LOW, MODERATE, HIGH}, corresponding to surfaces that are unsafe, moderately-unsafe, moderately-safe, or safe for traversal, respectively.

1. Introduction

Exploration of planetary surfaces and operation in rough terrestrial terrain have been strong motivations for research in autonomous navigation of field mobile robots in recent years. These robots must cope with two fundamental problems. The first problem is to acquire and analyze the terrain quality information on-line and in real time, and to utilize it in conjunction with limited prior terrain imagery. The second problem is to deal with imprecision in sensor measurement and uncertainty in data interpretation inherent in sensing and perception of natural environments. Because of these two fundamental problems, outdoor robot navigation defines a new research topic that is distinct from the conventional indoor robot navigation in structured and benign man-made environments.

Robust on-line terrain characterization and traversability assessment is clearly a core research problem for autonomous field robot navigation. Two types of solutions have been proposed to date by researchers at CMU and JPL. In the CMU methods [1-6], the robot traversability is computed along different arcs that correspond to different steering angles. The traversability of each arc is determined mathematically by a weighted sum of the roll, pitch, and roughness of the map cells along that arc, incorporating their certainty values [1]. The JPL approach [7-12] takes a sharp departure from analytical methods and is centered on the *Rule-Based Traversability Index*. This index is a novel concept that was introduced in [7-8] as a simple *linguistic* measure for quantifying the suitability of a natural terrain for traversal by a mobile robot. This perceptual approach to terrain assessment is highly robust to measurement noises and interpretation errors because of the use of fuzzy sets in a linguistic rule-based system. This approach is analogous to the human judgment, reasoning, and decision-making regarding assessment and traversal of a natural terrain.

Earlier papers by JPL researchers have focused on *regional* terrain characterization and traversability assessment, typically up to 5 meters away from the robot. In this paper, the traversability index concept is extended to both *local* and *global* terrain, to complement the regional measure. Sections 2-4 discuss terrain traversability analysis at local, regional, and global scales. The paper is concluded in Section 5 with a review of key features and areas of future research.

2. Local Traversability Analysis

For local traversability analysis, we focus on the terrain quality in close proximity of the mobile robot. Typically, this covers a distance of up to 0.5 meters away from the robot. The two attributes of the local terrain that contribute to its traversability are local obstacles and surface softness, as described below.

2.1. Local Obstacles

Local obstacle is the generic name that refers to large rocks ("positive" obstacles) or deep ditches ("negative" obstacles) that are impassable by the robot. Typically, a wheeled mobile robot with rocker-bogie design can go over obstacles 1-1/2 times its wheel diameter [13]. Smaller obstacles are therefore not considered as hazards to the robot mobility. Larger obstacles, however, impede the robot motion and must be considered. The presence of large obstacles can be detected in real-time by proximity sensors (for rocks) and cameras (for ditches) mounted on the robot [11]. Different types of proximity sensors can be used for this purpose, ranging from low-resolution infra-red sensors to high-resolution laser range-finders [see, e.g., 14], and the range of operation of these local sensors is typically 0.2 meters to 1 meter. Each local sensor (such as proximity sensor or camera) measures the distance d_o between the robot and the *closest* obstacle within its range of operation, and this information is continously updated during robot motion. The closest obstacle distance d_o is represented by three fuzzy sets with the linguistic labels $\{VERY-NEAR, NEAR, FAR\}$, with the trapezoidal membership functions shown in Figure 1a. Note that we can have different definitions of these membership functions for the front obstacle and the side (left and right) obstacles so that front and side traverse-local behaviors will have different sensitivities. Observe that *precise* measurement of the obstacle distance is *not* needed, because of the multi-valued nature of the linguistic fuzzy sets used to describe it.

2.2. Surface Softness

Local surface softness directly affects the traction of a mobile robot traversing a challenging terrain. Different ground material, whether soft sand, loose gravel, or compacted soil, exhibit different contributions to the robot's ability to travel effectively on the surface. For example, extremely gravely surfaces cause excessive wheel slippage, and thus are deemed unsafe for traversal. Soft sandy surfaces may cause the robot to sink, and should also be avoided. Surface material properties thus contribute directly to robot safety and must be included in local terrain assessment.

There are several methods for assessing the surface softness in close proximity of the robot. One concept is a non-contact sensor that consists of a pneumatic probe which will output a puff of air toward the ground surface and a laser displacement sensor that will detect the associated ground displacement. For "soft" ground, the detected surface displacement will be very large and for "hard" ground, the displacement value will be minimal. Another concept is a small force sensor carried by a simple mechanism attached to the robot that makes physical contact with the nearby surfaces and senses the resulting contact forces [15] (analogous to a blind person with a walking stick). These sensors will enable the robot to distinguish hazardous soft sandy region from safe hard compacted soil. Yet another method to determine the surface type, and as a result the surface softness, is based on visual texture analysis using neural networks [11]. This is a two-step approach; in the first step a neural network classifier is trained off-line using a set of known sample texture prototypes. In the second step, the trained neural network is used to recognize the ground texture acquired during run-time. The perceived surface type is then fed into a look-up table for obtaining surface softness γ. This softness factor is characterized by three fuzzy sets with the linguistic labels $\{SOFT, MEDIUM, HARD\}$, with the trapezoidal membership functions shown in Figure 1b. Again, observe that *precise* measurement of the surface softness is *not* needed, because of the multi-valued nature of the linguistic fuzzy sets used to describe it.

2.3. Local Traversability Index

Once the characteristics of the local terrain are obtained in terms of the closest obstacle distance d_o and local surface softness γ, this information can be incorporated into a single index of local traversability τ_l. This index is represented by four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, with the trapezoidal membership functions shown in Figure 1c. The relationship between the Local Traversability Index τ_l and the obstacle distance d_o and surface softness γ is expressed by a set of simple linguistic fuzzy logic rules. These rules are summarized in Table 1, with d_o and γ as two inputs and τ_l as the single output.

Observe that by utilizing fuzzy logic, the outcome of the rule set τ_l is *not* dependent on *exact* measurements of the obstacle distance d_o and the surface softness γ. This feature allows *robust* assessment and classification of the local terrain using imprecise sensors. This is because in the fuzzy logic formulation, the input variables d_o

and γ are allowed to vary over a range of values without altering the output variable τ_l.

3. Regional Traversability Analysis

The regional traversability covers a zone of typically up to 5 meters away from the mobile robot. The physical and geometrical qualities of the terrain segment within this zone determine its ease-of-traversal by the mobile robot. Several characteristics of the terrain can be considered for this purpose. The most notable ones are the terrain slope and roughness. These two characteristics are extracted from video image data obtained by the stereo cameras mounted on the mobile robot, as described below [11].

3.1. Terrain Roughness

The terrain roughness can be defined in several different ways. In this paper, we choose an intuitive approach by defining the region roughness in terms of the sizes and concentration of rocks in that region. The vision algorithm is applied to stereo camera images of the viewable scene to identify target objects located on the ground plane using a region-growing method [16]. Rock sizes are classified as $\{SMALL, LARGE\}$ depending on their pixel counts relative to a user-defined threshold. Rock concentrations are classified as $\{FEW, MANY\}$ depending on the number of rocks in the region relative to a user-specified limit. The terrain roughness is then determined based on the rock sizes and concentration in the region, and is represented by the four linguistic fuzzy sets $\{SMOOTH, ROUGH, BUMPY, ROCKY\}$, with trapezoidal membership functions. Table 2 summarizes the definition of terrain roughness in terms of rock sizes and concentration using a set of simple linguistic fuzzy logic rules.

3.2. Terrain Slope

To obtain the terrain slope from a pair of stereo camera images, we first calculate the real-world Cartesian x, y, z components of the ground plane boundary. Tsai's camera calibration model [17] is used to derive the relationship between the camera image and the real-world object position for a single camera. The images from both cameras are then matched in order to retrieve 3D information. The average slope value α is then determined using the equation $\alpha = \frac{1}{N}\sum_i^N atan2(z_i, x_i)$, where N is the number of points viewable in both images. The terrain slope α is represented by the four linguistic fuzzy sets $\{FLAT, SLANTED, SLOPED, STEEP\}$, with trapezoidal membership functions.

3.3. Regional Traversability Index

Once the characteristics of the viewable scene are extracted, the terrain traversal must be assessed. To accomplish this task, we have developed a set of fuzzy logic rules which assess the traversability of the terrain based on the characteristics present in the given image data set. The Regional Traversability Index encapsulates multiple terrain characteristics into a single index and succinctly quantifies the ease-of-traversal of the terrain by the mobile robot.

In order to characterize the terrain, the terrain characteristics are first converted into linguistic representations using fuzzy sets. These sets allow each terrain characteristic to be represented based on *grades* of membership to user-defined linguistic fuzzy sets. The membership functions of these sets are then used in a set of fuzzy logic rules to infer terrain traversability. The output from the rule base is the Regional Traversability Index which represents the relative level of safety associated with traversing the viewable area. This index is represented by four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, with trapezoidal membership functions. By utilizing fuzzy logic, the user can specify rules that are not dependent on *exact* measurements of the terrain characteristics, thus allowing *robust* analysis of the terrain. These simple fuzzy relations are summarized in Table 3.

4. Global Traversability Analysis

In previous sections, we present local and regional traversability analyses using on-board sensors, with ranges of resolution typically 0.5 meters and 5 meters. In this section, a different type of terrain traversability is discussed which is based on the *terrain map* and operates in tens of meters resolution.

4.1. Global Traversability Map

The Global Traversability Map classifies the terrain segments based on how difficult and unsafe each segment is for traversal by the mobile robot. The map building process involves two steps. We first identify relevant topographic terrain features (such as ravines, mountains, and valleys) as observed in aerial imagery, which contribute to traversal difficulty. Various image-based techniques can be used to identify these relevant terrain features. For example, to identify ravines, an approach can be utilized which locates curving linear features embedded in the image using edge-detection techniques [18]. For identifying mountains and hills, the peaks and valleys can be found based on contour lines [19].

Once the relevant topographic terrain features are extracted, they are fed into a linguistic rule set for constructing the Global Traversability Map. This map grades the level of risk (or safety) associated with traversal over a given terrain segment by using a multi-valued [0, 1] index.

Each segment of the terrain map is assigned a Traversability Index that reflects the terrain quality for traversal. The segment classification can be performed using four fuzzy sets with the linguistic labels $\{POOR, LOW, MODERATE, HIGH\}$, as in Sections 2-3, with trapezoidal membership functions. Each traversability class designates the traversal risk/difficulty associated with that segment, namely unsafe, moderately-unsafe, moderately-safe, and safe.

For example, a large gorge can easily be designated as untraversable, and thus will receive a POOR traversability index; whereas a mountain or a hill depending on the slope may receive a POOR to MODERATE traversability index. Note that while the mountain peak has a POOR traversability value, as we move down slope to the foothills, the traversability can change to LOW and MODERATE. Therefore, the mountain can be characterized by a set of three concentric circles with different traversability indices as shown in Figure 2a.

We define a fixed map-based $\{x, y\}$ coordinate frame-of-reference. At any time, the robot is aware of its own coordinates on the traversability map using its start position and the encoder counts of its wheel motors or using any localization method. Typically, the robot start position is taken to be the origin of the coordinate frame for simplicity. To represent the Global Traversability Map to the robot navigation system, the user can, for instance, choose any of the following two representations:

- *Traversability Regions:* Each segment is approximately bounded by the coordinate inequalities $\{X_{min} \leq x \leq X_{max}, Y_{min} \leq y \leq Y_{max}\}$, as shown in Figure 2b. This, in effect, defines the rectangular area in the terrain map that is occupied by the particular feature. Alternatively, each segment is enclosed by a geometric shape such as a circle. The enclosing circle is mathematically described by $(x-a)^2 + (y-b)^2 = r^2$, where (a, b) are the center coordinates and r is the radius–an example is shown in Figure 2b.

- *Traversability Grid:* We overlay on the map an MxN grid composed of MN equal-sized grid cells, where M and N are user-defined numbers chosen based on the map resolution and the robot footprint. Each grid cell is assigned a traversability index that reflects the *minimum* index of all terrain segments occupying that cell (see Figure 2c).

The procedure for generation of the Global Traversability Map is carried out *off-line*. Once this map is generated, its mathematical model is down-loaded in the memory of the computing platform mounted on the robot. From the robot navigation perspective, the Global Traversability Map is available to the robot navigation system *prior* to the robot movement.

4.2. Global Traversability Index

Once the Global Traversability Map is generated, we can compute the Global Traversability Index of the mobile robot in different directions at any time. For this purpose, we proceed as follows:

- Decompose the terrain traversable by the mobile robot into several circular sectors centered at the current robot position and having radius R_g. The value of R_g determines the *reaction distance* of the robot and is the distance at which we wish the robot to react to the global surface features.

- For each circular sector, assign the *minimum* traversability index of the map segments contained within that sector. This can be obtained using geometric calculation of the intersections between the sector and the segments. The rationale for using the minimum index is to enhance robot safety, given the fact that the map information and terrain classification are often inaccurate and approximate.

The outcome of this procedure is the global traversability index τ_g that corresponds to a particular sector.

5. Conclusions

Multi-scale traversability indices are introduced in this paper for a field mobile robot operating on a challenging natural terrain. These indices quantify the difficulty/risk associated with the robot mobility at three scales of resolution. Terrain-based navigational behaviors based on traversability indices are critical components of any field robot navigation strategy. These behaviors provide a means for incorporating different terrain characteristics into the robot navigation logic. Current research is focused at implementation and field testing of the methodology described in this paper on a Pioneer all-terrain mobile robot.

6. Acknowledgements

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7. References

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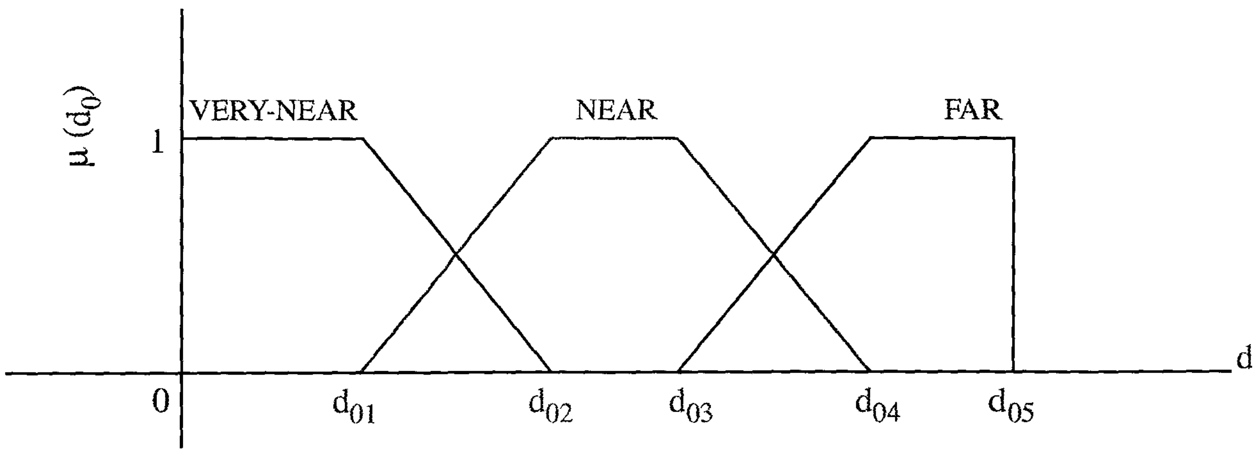

Figure 1a. Membership functions for obstacle distance d_0

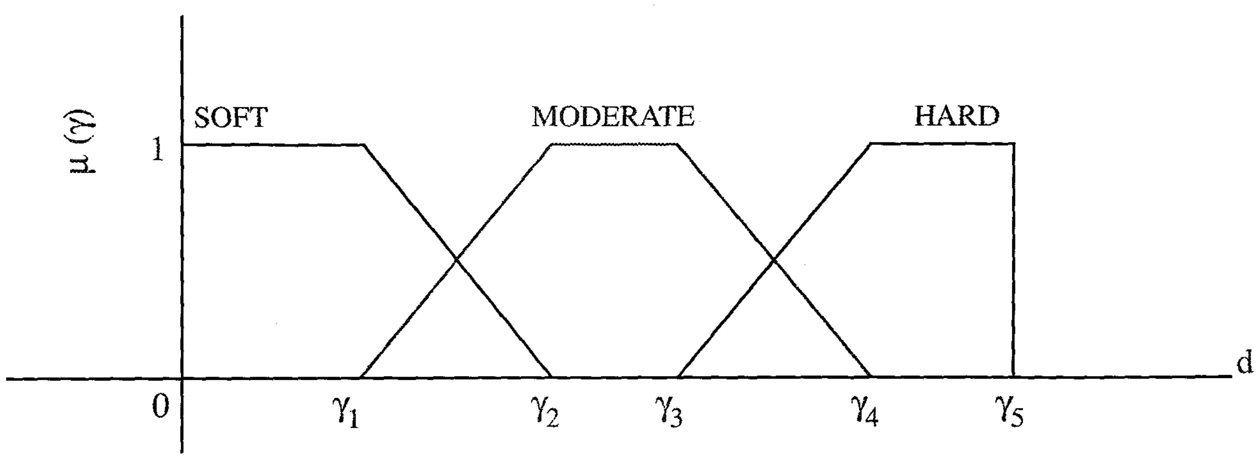

Figure 1b. Membership functions for surface softness γ

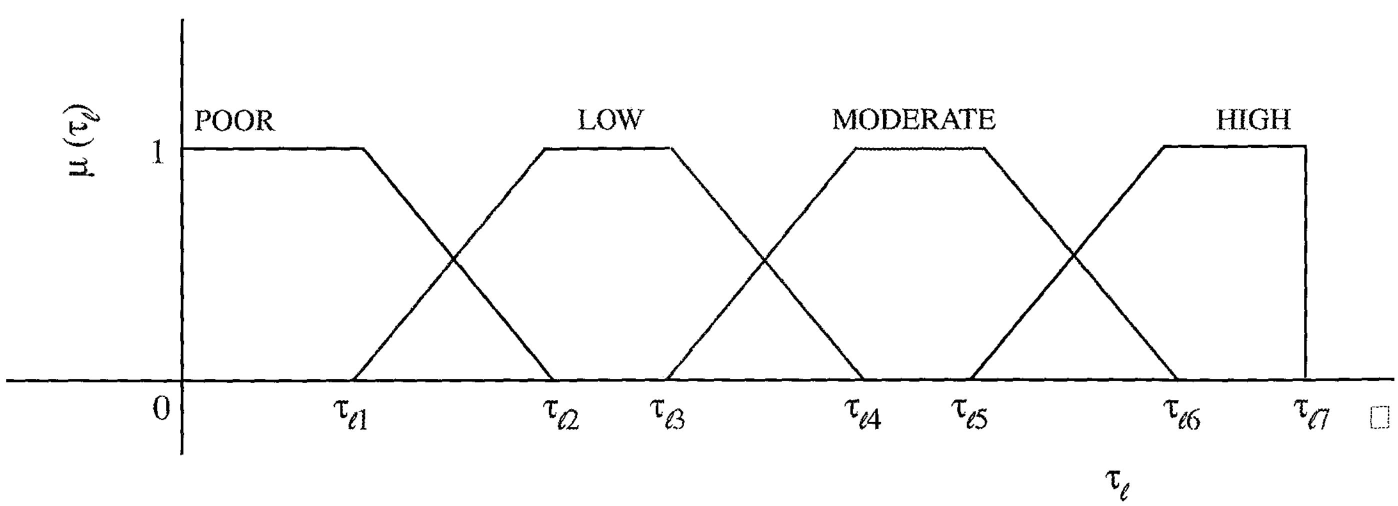

Figure 1c. Membership functions for local Traversability Index τ_ℓ

Surface Softness \ Obstacle Distance	Far	Near	Very-Near
Hard	High	Moderate	Poor
Medium	Moderate	Low	Poor
Soft	Poor	Poor	Poor

Table 1. Rule set for Local Traversability Index

Rock Concentration \ Rock Size	Small	Large
Few	Smooth	Bumpy
Many	Rough	Rocky

Table 2. Rule set for Terrain Roughness

Terrain Slope \ Terrain Roughness	Smooth	Rough	Bumpy	Rocky
Flat	High	High	Moderate	Poor
Slanted	High	Moderate	Low	Poor
Sloped	Moderate	Low	Low	Poor
Steep	Poor	Poor	Poor	Poor

Table 3. Rule set for Regional Traversability Index

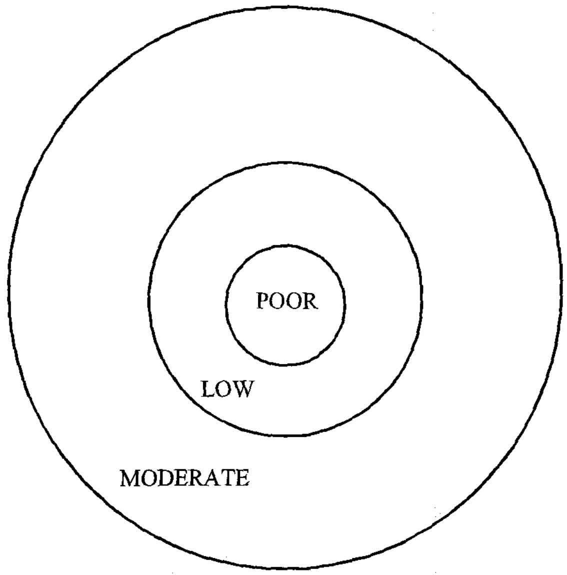

Figure 2a. Traversability map representation of a mountain or a hill

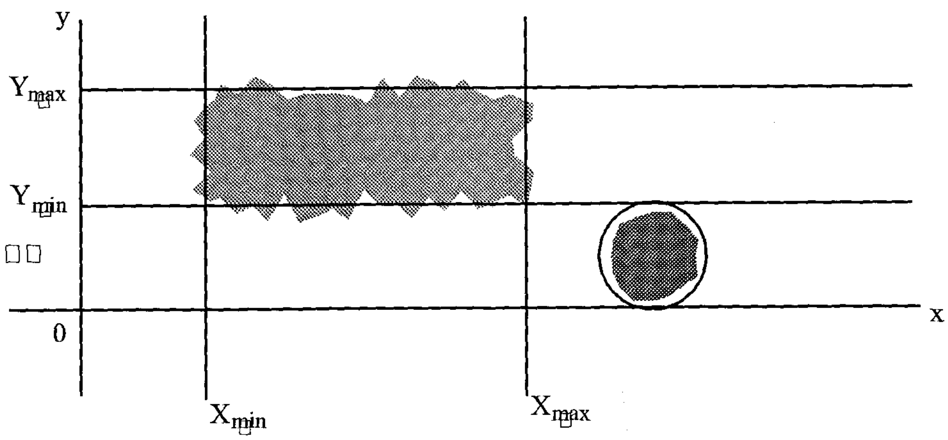

Figure 2b. Representation of traversability regions in a map

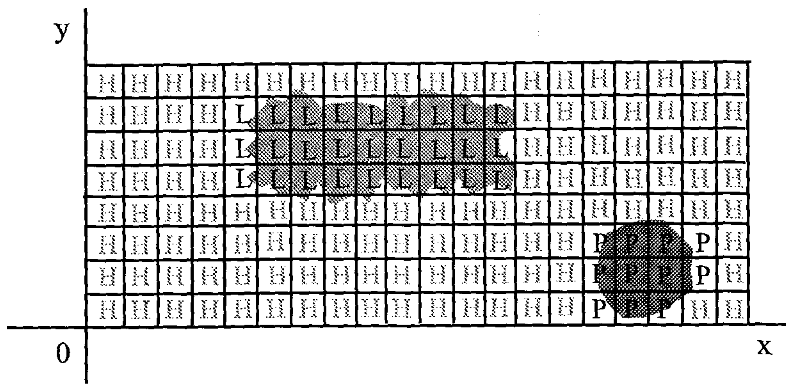

Figure 2c. Overlay of a traversability grid on a map